Transportation Research Part D 69 (2019) 168–183

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Impacts of severe weather events on high-speed rail and aviation delays

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ARTICLE INFO

Keywords:
Aviation
High-speed rail
Delay
Vulnerability
Severe weather event
On-time performance

ABSTRACT

Transportation systems have become much more vulnerable due to the increased amount of unexpected severe weather events caused by the effects of climate change. One of the direct consequences is that the punctuality of transportation systems is severely affected and the prediction of the on-time performance of scheduled service becomes challenging due to the uncertainty of severe weather's occurrence. The objective of this paper is to investigate two fundamental questions pertaining to the operational reliability of passenger transportation systems, using high-speed rail (HSR) and aviation in China as an example: what are the impacts of severe weather events on HSR and aviation delays, and to what extent are these systems vulnerable to various types of severe weather events? To address these questions, a dataset with 350,000 detailed, on-time performance records of HSR and air services for the period October 2016–September 2017 was adopted. Based on data visualization and statistical analysis, the study reveals that the impacts of severe weather events on HSR and aviation's on-time performance vary spatially and temporally. In general, HSR is less vulnerable than aviation to most severe weather events. In terms of the spatial variation, the operation of HSR in the southeast coastal region is affected more frequently by rain and thunderstorms, whereas the system operated in central-eastern China is more vulnerable to snowstorms.

1. Introduction

Transportation systems are facing unprecedented challenges due to the uncertainty of severe/extreme weather events caused by climate change. Major events such as hurricanes, thunderstorms, and winter storms occur more frequently now than they did decades ago. These events not only cause direct damage to transportation infrastructures, but also lead to indirect economic consequences as a result of the disruption of transportation services. For instance, Tyndall (2017) showed that unemployment in neighborhoods in New York City affected by Hurricane Sandy increased 1.4% due to the storm's disruption of the subway system. Chen and Rose (2018) revealed that the negative economic consequences of Hurricane Katrina were substantial due to transportation system failures. In China, the transportation system is observed to be disrupted more frequently by extreme weather events such as tropical storms. For instance, HSR services and over 350 flights in major cities in South China were completely cancelled during Typhoon Nida. Likewise, the 2008 ice storm caused a large scale and severe disruption of the transportation system as over 5.8 million travelers were stranded and the direct economic losses totaled $22.3 billion (Zhou et al., 2011).

Although it is generally recognized that transportation planning and management agencies need to improve system resilience in

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https://doi.org/10.1016/j.trd.2019.01.030

Available online 14 February 2019
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order to reduce losses and disruptions to the greatest extent possible, it is challenging to identify appropriate implementation strategies to reduce the negative consequences of disruptions. This is partially attributable to the lack of a valid understanding of the impacts of severe/extreme weather events on transportation system performance. In particular, it is unclear how impacts vary among different types of events, as well as how they vary spatially and temporally for different modes of transportation during the same event.

This paper addresses these aforementioned questions with a focus on two transportation modes in China: high-speed rail (HSR) and aviation. The motivation for such a focus originates from the competitive nature of these two systems in the Chinese market.[1] Although air and passenger rail used to be non-competitive, since air generally serves medium to long-distance travel while rail has the advantage of short-distance travel, the massive development of the HSR network system in China has fundamentally changed the intercity travel market structure. In particular, the Chinese HSR system has unique advantages in terms of train speed (faster than trains in Europe and East Asia), network connectivity (which allows for more opportunities to connect and transfer through the 4-by-4 network corridor), and scale of service (accounting for two-thirds of the world's HSR network). These factors have made the two modes become competitive in a much wider distance range.

Furthermore, Wei et al. (2017) and Wang et al. (2018) found that air traffic and fare can be very sensitive to HSR speed, and Wan et al. (2016) found that they are also sensitive to the network structure of HSR. As a consequence, while the impact of HSR on airlines was traditionally considered to be the greatest on route distances between 500 and 800 km (e.g., Chen, 2017), Zhang and Zhang (2016) found that Chinese HSR can be an effective competitor for airline routes up to 1300 km. In addition, based on a survey conducted in China, Wang et al. (2018) further suggested that HSR is the most effective mode for distances in the 500–1500 km range. These evidences, together with the worsened on-time performance (OTP) of air flights discussed in this paper, will provide an improved justification for looking at the rail-air competition in China and help both transportation planners and decision-makers better understand the competitive nature of the two modes under environmental (weather) conditions.

Hence, the objective of this research is to examine how the punctuality of HSR and the aviation system differs during various extreme weather events. To begin, a dataset with detailed information regarding on-time performance of these two transportation modes was adopted for an empirical assessment. The clarification of these questions are fundamental for at least two reasons. First, it helps to advance the risk management of transportation agencies by improving their understanding of the system's vulnerability to various types of severe weather events. Second, the research findings can also help transportation planners better understand how reliable different transportation modes are under various weather conditions. Subsequently, they will be able to further enhance the adaptive resilience of the economic system by developing strategies to improve the general public's awareness of modal substitution under severe/extreme weather events.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces data and methodology. Section 4 presents data visualization and descriptive analysis, whereas Section 5 discusses the results of the regression analysis. Section 6 concludes and summarizes.

2. Literature review

With the global environment getting warmer due to an increase in greenhouse gas emissions, the number of extreme weather events is also on the rise. For instance, as discussed by Coffel et al. (2017), climate change leads to various negative consequences such as the generation of more extreme precipitation events (O'Gorman and Schneider 2009; Kharin et al., 2007), the alteration of mid-latitude storm tracks (Yin, 2005; Coumou et al., 2015), changes in the frequency and intensity of hurricanes (Knutson et al., 2010; Webster et al., 2005), and other types of disruptions due to prevailing weather patterns.

Disruptions of transportation services caused by severe/extreme weather events have also become more frequent in recent years. In fact, weather is considered the primary factor for airline delays both in the U.S. (Federal Aviation Administration, 2018) and China (Chen et al., 2018). This is because severe weather conditions have a direct influence on airport capacity and flight route, which can cause cascading delays throughout the entire aviation system (Lan et al., 2006; Fleurquin et al., 2013).

Based on these facts, a plethora of studies has attempted to examine the linkage between weather conditions and transportation system performance from an engineering perspective (Cools et al., 2010a; 2010b; Meyer et al., 2012; Wang et al., 2015; Diakakis et al., 2016). While the aviation sector is a major focus in these studies, relatively less attention is given to the impact of severe weather on other transportation modes. Studies regarding the comparison of the impact of extreme weather events among different modes of transportation are even scarcer. One of the reasons for such a limitation, as explained by Jaroszweski et al. (2010), is the lack of an interdisciplinary approach to examine the issue by taking both climate and socioeconomic scenarios into account.

Among the exceptions, Taylor and Philp (2010) provide a qualitative assessment of the impact of climate change on land-based transportation infrastructure, systems, and behavior in Australia. Although their work emphasizes that the key for transportation to be adaptive is to understand system vulnerability and develop resilience, it remains unclear how these issues can be assessed quantitatively. Koetse and Rietveld (2009) provide a comprehensive review of the effects of climate change and weather conditions on the transportation sector. Specifically, they indicate that assessing the influence of climate change on a transportation system can be conducted using three approaches. The first is to compare transportation systems between regions with very different climate conditions; the second is to examine the impact of climate change through an understanding of seasonal variations in transportation service; and the third is to examine the relationship between weather and travel behavior.

[1] We appreciate the valuable suggestions received from one of our reviewers.

Table 1
Summary of the relevant empirical studies examining the impact of extreme weather events on transportation performance.

Authors	Area	Hazard type	Data	Method	Focus
Suarez et al. (2005)	Boston, U.S.	flood	Hypothetic data	Traffic Simulation	Assesses the potential impact of climate change on the system-wide performance of transportation networks
Panteli & Mancarella (2017)	n/a	multi-hazards	Hypothetic data	Sequential Monte Carlo simulation	Provides a conceptual framework for gaining insight into the resilience of power systems
Cools et al. (2010b)	Belgium	Multi- weather	Survey data	Discrete Choice	Examines whether the type of weather influences the likelihood of a change in travel behavior and whether changes in travel behavior due to weather conditions are dependent on trip purpose
Zanni et al. (2017)	U.K.	Severe weather	Survey data	Discrete Choice	Evaluates the impact of a changing climate on long distance travel and mobility between London and Glasgow
Lu et al. (2014)	Bangladesh	flood	Survey data	Discrete Choice	Investigates how people adapt their inter-city travel behavior to flooding in Bangladesh
Stamos et al. (2015)	European cities	Severe weather	Hypothetic	Discrete Choice	Assesses the resilience of the European passenger transport network during severe weather events using a data-driven approach
Maze et al. (2006)	U.S.	Severe weather	Mixed data	Traffic simulation	Identifies the linkages between highway accidents and severe weather conditions
Abkowitz et al. (2017)	Tennessee, U.S.	Storm, heat wave	Survey data	Indicator approach	Vulnerability assessment of transportation infrastructure to severe weather events
Rowan et al. (2013)	Mobile, AL	Multi-hazards	Literature review	Indicator approach	Introduces a sensitivity matrix to screen for assets that are sensitive and vulnerable to climate change
Molarius et al. (2014)	Europe	Multi-hazards	Literature review	Indicator approach	Develops an extreme weather risk indicator to measure the risk to European transportation systems to extreme weather events
Mitsakis et al. (2014)	Greece	Wildfire	Secondary data	Case study and GIS	Presents an overview of infrastructural damages and human injuries and losses resulting from the 2007 wildfire in Greece.

Source: Authors' summary.

Table 1 summarizes the most relevant studies that examine the impact of extreme weather events on transportation system performance. One fact worth noting is that the impact of severe weather events on transportation systems has been investigated extensively from the demand perspective. For instance, Tsapakis et al. (2013) examine the influence of severe weather events such as heavy rain and snow on urban travel time changes, with a focus on the greater London area. Their study found that severe weather has a strong influence on urban transportation demand due to travel time delay. Similarly, Zanni et al. (2017) examine the impact of extreme weather events on long distance travel and mobility between London and Glasgow using a discrete choice modeling method. Based on data from online survey, they confirmed that weather-related disruptions negatively affect travel demand change. Similarly, Lu et al. (2014) evaluate how people adapt their inter-city travel behavior during severe weather events in Bangladesh using a flood event as an example. They found that travel demand is likely to decrease significantly as roads are disrupted by flooding.

In other studies, the impacts of extreme weather events on transportation are generally evaluated through various indicators. For instance, Rowan et al (2013) and Abkowitz et al. (2017) evaluate the risk of transportation infrastructure assets to various weather events in the US. A similar approach is also applied by Molarius et al. (2014) to measure the risk to the transportation network from extreme weather events in Europe. Although the indicator approach provides transportation agencies with a straightforward method to understand the risk of transportation assets to various extreme weather events, it has a major limitation in that the result could be arbitrarily determined, as the criteria of measurement are often derived from experts' judgements or experiences. In addition, there is also a lack of systematic consideration of the statistical association of various events on the performance of transportation systems.

Another study worth nothing was conducted by Stamos and Mitsakis (2014), who evaluate the transportation-related adaptation measures and policy actions for addressing climate change through a case-study review. Although the varying strategies adopted by different modes of transportation were summarized, the study did not provide an in-depth comparison of how different transportation modes reacted given the occurrence of specific extreme weather events.

Overall, the literature review suggests that although the influence of weather and climate change on a single mode of transportation has been examined extensively, very few studies focus on assessing the impacts of various severe weather events from a modal comparative perspective.

Furthermore, although the indicator approach may help emergency management agencies recognize the vulnerability of transportation to severe weather events from an *ex ante* perspective, it remains unclear how the operational performance of transportation systems may vary among different weather events from an *ex post* perspective. In other words, it is unclear to what extent transportation systems are vulnerable to different weather events based on data reflecting the actual performance of the system.

Lastly, although several studies have examined the impact of extreme weather on transportation from the demand-side perspective, the investigation of this issue from the supply-side with a focus on assessing how on-time performance of transportation systems is affected by severe weather events remains scant.

3. Data and methodology

The process of data analytics is illustrated in Fig. 1. Specifically, daily weather information was collected from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA). The data of aviation delays and cancellations was obtained from Variflight, which is an information technology company specializing in civil aviation data services. Data of HSR's on-time performance record was collected from the official Weibo (a Chinese version of Twitter) of the Shanghai Railway Bureau. The system provides updates on the delays of high-speed trains (known as D-train and G-train) every two hours. The data includes all the high-speed trains that operate on the routes managed by the Shanghai Railway Bureau. This data provides affluent information to capture the detailed operational performance of HSR that either connects directly to Shanghai or is adjacent to the Shanghai area.

The data processing was implemented in the following steps. First, raw data representing HSR delays for the period of October 1, 2016–September 30, 2017 was downloaded using a web-crawling technique from the Weibo of the Shanghai Railway Bureau. Since the raw data was presented in a JPG format, the Optical Character Recognition (OCR) technique was adopted to convert the information into text format. Next, the data was further refined and classified using Artificial Intelligence techniques. Specifically, the Natural-language processing (NLP) technique was applied to convert the text format data into a database format using the

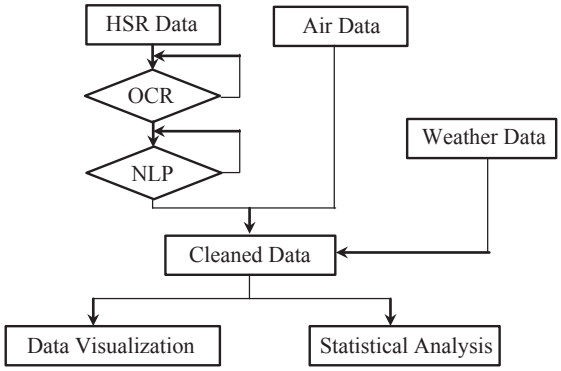


Fig. 1. Process of the data analytics.

Table 2
The select HSR and aviation services by different routes.

Route	Beijing- Shanghai	Hangzhou – Shenzhen	Bengbu – Hefei
Number of Different HSR services	757	220	61
Number of Total Scheduled HSR Services	130,716	59,400	27,538
Number of Daily Average Scheduled HSR Service	352	161	76
Number of Different Air Services	30	6	29
Number of Total Scheduled flights	71,276	26,642	34,081
Number of Daily Average Scheduled Air Service	195	73	93

Source: Authors' calculation.

Levenshtein distance (edit distance) as a similarity metric for the classification of information. Thirdly, the daily on-time performance of each HSR line was calculated using the maximum number of delayed trains divided by the total number of scheduled trains of each route in a given day. Meanwhile, the raw data reflecting aviation delays and cancellations was processed by calculating the following metrics for each route each day: the number of delayed flights at arrival, the number of cancelled flights, and the average OTP of arriving flights.

The definition of OTP differs slightly between HSR and aviation. For instance, the Civil Aviation Administration in China considers a flight to be on time if its gate-departure/arrival time is within a 30-minute window of its scheduled departure/arrival time, whereas a high-speed train is considered on time if the difference between the actual departure/arrival time and the schedule is < 5 min. Hence, the average OTP of air travel and high-speed trains for a given route from city i to city j in day t is calculated through the following equation:

$$OTP_{ij,t} = \frac{TNSS_{ij,t} - TNDS_{ij,t}}{TNSS_{ij,t}} \tag{1}$$

where *TNSS* represents the total number of scheduled services and *TNDS* represents the total number of delayed services.

To examine how the impact of severe weather events on HSR and the aviation system may vary among different regions, three HSR lines were selected: the Beijing- Shanghai line, the Hangzhou-Shenzhen line, and Bengbu-Hefei line. The selection was based on the consideration of data availability and the representation of different regions. This enables us to capture the heterogeneous characteristics of climate conditions in different regions. The first two corridors were selected to represent the long-haul HSR systems operating in the Northern and Southern parts of China, respectively, whereas the latter one represents a short-haul HSR that operates in the Central-Eastern region. In the final step, the performance data of HSR and aviation services in the same corridor were merged with the corresponding daily weather data. The summary statistics of the select HSR and aviation services are illustrated in Table 2. The detailed descriptive statistics of the merged data representing the three corridors are summarized in Appendices A–C.

The assessment consists of descriptive analysis through data visualization and statistical regression analysis. The objective of the first part is to understand how the OTP of different transportation modes varies temporally and spatially, whereas the second part of the assessment focuses on investigating whether the statistical associations of the operational performance of HSR and the aviation system may differ under various weather conditions. Specifically, the empirical models to be estimated are illustrated as follows:

$$\begin{aligned} Y = {} & \beta_0 + \beta_1 * lag.\ Y + \sum_{i=1}^{n} \beta_{2,i} * Precipitation_i + \sum_{i=1}^{n} \beta_{3,i} * Fog_i + \sum_{i=1}^{n} \beta_{4,i} * Thunder_i + \sum_{i=1}^{n} \beta_{5,i} * Snow_i + \sum_{i=1}^{n} \beta_{6,i} * Wind_i + \beta_{7,i} * Press1_i + \beta_{8,i} * Press2_i \\ & + \beta_9 * Oct + \beta_{10} * Nov + \beta_{11} * Dec + \beta_{12} * Jan + \beta_{13} * Feb + \beta_{14} * Mar + \beta_{15} * Apr + \beta_{16} * May + \beta_{17} * Jun + \beta_{18} * Jul + \beta_{19} * Aug + \varepsilon \end{aligned} \tag{2}$$

where n represents the number of key cities in each case. Y denotes the performance of HSR and air, which is measured by three dependent variables: OTP, number of delayed services, and number of cancelled services, respectively. The independent variables include a lagged-term of the dependent variable, which is introduced to control for the effects of the delay from the previous day. Following the example of Alderighi and Gaggero (2018), the weather conditions captured in the analysis include the amount of precipitation and whether or not the following weather is present in city i, respectively: fog, thunder, heavy wind, and snow. Given that the atmospheric pressure variables were found to be highly correlated among different cities in the case of the Beijing – Shanghai corridor and the Hangzhou – Shenzhen corridor (as illustrated in Appendices D and E), a factor analysis was introduced to extract the factors that affect the variations of atmospheric pressure. The rotated factor loadings of the pressure variables in different cities, as summarized in Table 3, reveal that the influence of atmospheric pressure can be decomposed into two factors, named Prea 1 and Prea 2.[2] These two variables were introduced to control for the influence of atmospheric pressure. In addition, the dummy variables that represent different months are also introduced to control for the temporal effect due to the change in travel demand.

[2] The Federal Aviation Administration (2016) indicates that temperature and altitude are the two key factors affecting the pressure of the atmosphere.

Table 3
Factor analysis results for atmospheric pressure.

Route	Beijing - Shanghai Corridor			Hangzhou - Shenzhen Corridor			
City (Variable)	Factor1	Factor2	Uniqueness	City (Variable)	Factor1	Factor2	Uniqueness
Beijing (pek_prea)	0.530	0.837	0.018	Hangzhou (hgh_prea)	0.602	0.752	0.073
Shanghai (sha_prea)	0.835	0.538	0.013	Fuzhou (foc_prea)	0.704	0.701	0.014
Nanjing (nkg_prea)	0.808	0.584	0.006	Shenzhen (szx_prea)	0.758	0.606	0.058
Jinan (tna_prea)	0.602	0.794	0.008				

Notes: The table reflects rotated factor loadings (pattern matrix) and unique variances. The atmospheric pressure is measured in psi in the original variables. The correlation values between factors 1 and 2 are 0.044 and 0.595 in the Beijing-Shanghai corridor and Hangzhou-Shenzhen corridor, respectively.

4. Data visualization and descriptive analysis

Fig. 2 presents a screenshot of the visualization platform, which was developed based on Google Map. The existing system is still preliminary, as it only enables users to compare the change of OTP of select HSR and air services under different weather conditions on any given day during the period of October 2016–September 2017. However, the purpose here is to demonstrate an important application based on detailed performance data from aviation and HSR, in order to allow a dynamic comparison of air-HSR OTP under different weather/environmental conditions. One should also note that such a platform has the potential to reveal more detailed comparisons of air-HSR performance by differentiating the direction of transportation services and the departure and arrival punctuality. The ultimate goal is to allow transportation planners and management agencies to not only track the performance of air-HSR in real time by connecting the system with the corresponding data sources, but also to enable them to forecast the OTP of these systems under different extreme weather conditions. Such a system would be especially important for risk and emergency management, and also for decision-making to enhance system resilience.

The temporal variations of HSR's OTP are also compared with that of the air services in the given corridors. As illustrated in Fig. 3, the OTP of HSR and aviation serving the same OD tends to be quite different. For instance, the OTP of Beijing – Shanghai HSR is found to be much higher than that of aviation. In terms of variation over time, the OTP of HSR tend to be more consistent than that of aviation. While the average OTP of HSR tends to be generally above 0.8, the variation of aviation's OTP tends to be quite significant. Specifically, while it appears that the OTP of arriving flights between Beijing and Shanghai tends to be relatively higher during the winter months, the rate does fluctuate substantially during the summer months of May and August. This suggests that the OTP of transportation systems is influenced strongly by temporal factors such as weather and travel demand changes.

In terms of regional variation, Fig. 3 also reveals that the OTP of HSR and aviation operating in the Beijing – Shanghai corridor

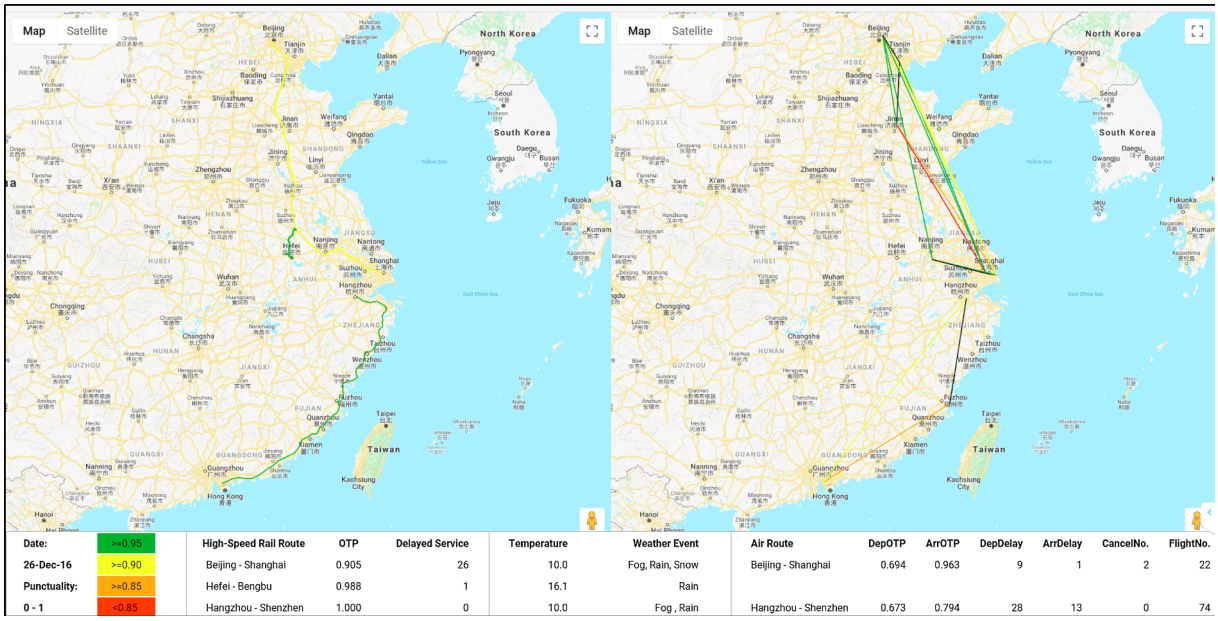
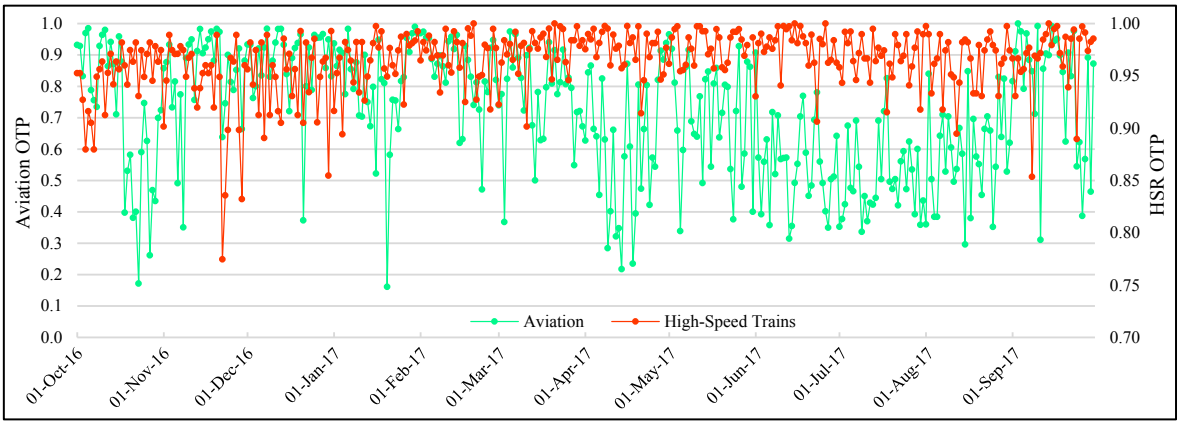
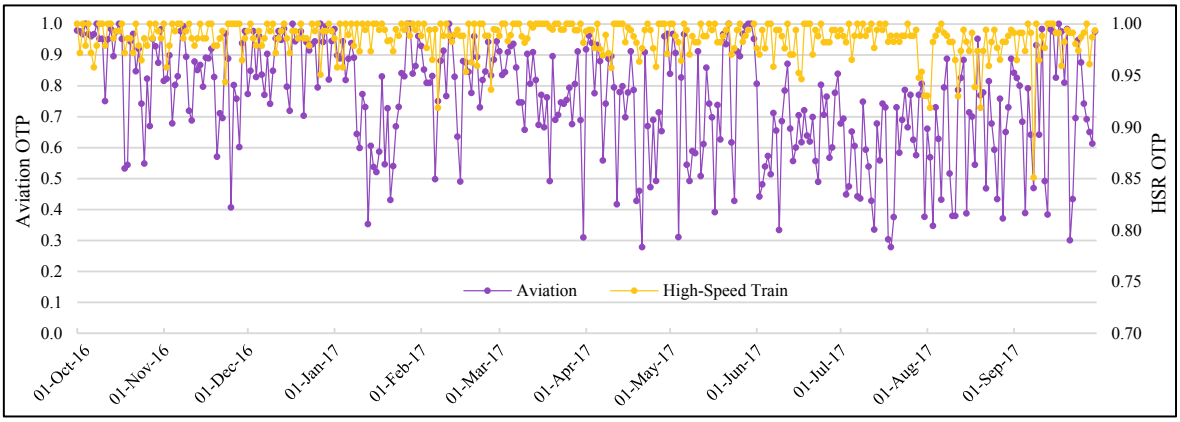


Fig. 2. Visualization of delayed HSR and air services in select routes. Note: The direction of transportation service in each route is not differentiated in this preliminary version. Hence, the different colors of lines represent the average OTP of each route in the given day only. Source: Authors' design. Readers who are interested in exploring this platform may visit our site at: www.norman.cloud/visualization.



(a). The Beijing - Shanghai Corridor



(b) The Hangzhou – Shenzhen Corridor

Fig. 3. Temporal variations of on-time performance of select HSR and air routes. Notes: The OTP of air services in (a) reflects the average performance of the following flights: Beijing (PEK) – Shanghai Hongqiao (SHA), PEK – Shanghai Pudong (PVG), SHA – PEK, and PVG – PEK. The OTP of air services in (b) reflects the average performance of the following flights: Hangzhou (HGH) – Shenzhen (SZX) and SZX – HGH. Source: Authors 'summary.

and the Hangzhou – Shenzhen corridor tend to be dissimilar, suggesting spatial heterogeneous characteristics do exist among these different systems.

To further understand how the operational performance of HSR and aviation may be affected by different extreme weather events, Table 4 summarizes the operational performance of the two systems under two types of extreme weather events – typhoons and snowstorms. Specifically, the operational performance was compared in terms of the average OTP, the number of cancelled and delayed services, and the daily average delayed minutes per service during the extreme weather event. For instance, during Typhoon Hato, the operational performance of both air and HSR were severely affected. Specifically, the average OTP of flights between Shenzhen (SZX) and Hangzhou (HGH) reduced substantially, from 0.9 in Day 1 to 0.29 in Day 4, as the cyclone became stronger and moved closer to the coastal area. Meanwhile, other indicators such as the number of cancellations and delayed minutes also experienced substantial increases as the magnitude of the cyclone amplified. Conversely, although the performance of HSR in the same corridor was also affected by Typhoon Hato, the influence was relatively small compared to that of air services. For instance, the average OTP only decreased from 0.97 to 0.92 during the first two days of the event; the overall performance was much better than that of aviation. In terms of cancellations, the disruption of HSR was also less severe than that of aviation; only 14 of the 172 scheduled services were cancelled when the typhoon made landfall on August 23. However, it should be noted that the event did cause heavy delays of high-speed train (HST) services. The worst delay occurred on the second day of the event, when the average delay of the 14 HSTs serving the Shenzhen – Hangzhou corridor was over 4 h.

It is worth noting that HSR appears to be more resilient than aviation to the disruption of typhoons. The OTP of HSR recovered to 0.98 immediately as the storm weakened after landfall. Conversely, OTP of the corresponding aviation services remained relatively low, even after the storm dissipated on August 24.

Table 4 also shows that the performance of aviation and HSR tends to vary during snowstorms. For instance, on the first day of the snowstorm that occurred in November 2016, 42 flights between Beijing and Shanghai experienced a delay, with an average of 42 min. Conversely, only 12 HSTs experienced a delay, with an average of only 12 min. The most significant impact on HSR was during the second day of the snowstorm as OTP decreased to 0.78 and the number of delayed services increased to 62, with an average delay of

Table 4
Comparison of operational performance between aviation and HSR during different extreme weather events.

Event	Corridor	Date	Aviation				High-Speed Rail			
			OTP	Cancelled flight	Delayed flight	Delayed minutes	OTP	Cancelled HST	Delayed HST	Delayed minutes
Typhoon Hato[a]	Shenzhen - Hangzhou	19-Aug-17	0.90	0	12	104	0.97	0	3	95
		20-Aug-17	0.52	3	28	65	0.92	0	14	288
		21-Aug-17	0.81	0	12	34	0.97	0	3	126
		22-Aug-17	0.29	13	35	135	0.99	0	1	51
		23-Aug-17	0.34	27	23	217	0.95	14	7	128
		24-Aug-17	0.33	2	40	97	0.98	0	2	40
		25-Aug-17	0.42	2	35	107	0.99	0	1	6
		Average	0.52	7	26	108	0.97	2	4	105
Snowstorm[b]	Beijing - Shanghai	**21-Nov-16**	0.60	11	42	42	0.96	0	12	12
		22-Nov-16	0.74	4	30	34	0.78	0	62	104
		23-Nov-16	0.90	4	12	42	0.84	0	45	46
		24-Nov-16	0.81	0	22	46	0.90	0	28	35
		25-Nov-16	0.78	2	25	27	0.97	0	9	12
		26-Nov-16	0.85	2	17	28	0.96	0	10	9
		27-Nov-16	0.92	0	9	18	0.99	0	3	13
		Average	0.80	3	22	34	0.91	0	24	33

Source: Authors' collection and calculation.

[a] Typhoon Hato was a tropical cyclone that struck South China in August 2017. It formed on August 19 and was further developed into a storm the next day. Hato became a Category 3 equivalent typhoon on August 23 before making landfall over Zhuhai in the Guangdong province. The storm then weakened over land and dissipated on August 24 (Takagi et al., 2018).

[b] The snowstorm, which started on Nov 21 and ended Nov 27, 2016, affected many regions in the central eastern and northern regions of China.

104 min. Conversely, 30 flights were delayed and 4 flights were cancelled due to the inclement weather. In general, the comparison shows that the HSR system appears to be less affected than aviation in terms of OTP, service cancellation, and delays during snowstorms.

5. Regression analysis

The regression analysis was conducted to investigate the influences of various weather conditions on the operational performance of HSR and aviation using the time-series data. Table 5 summarizes the regression results of weather impacts on HSR and aviation's performance, with a focus on the Beijing - Shanghai Corridor. To capture the spatial heterogeneous effects, weather conditions in the four major cities (Beijing (PEK), Shanghai (SHA), Nanjing (NKG), and Jinan (TNA)) along the corridor were controlled.[3] Specifically, Models 1 and 2 reveal that weather conditions do have significant impacts on the variations of HSR's OTP.[4] For instance, the amount of precipitation in Beijing was found to be negatively associated with the change of HSR's OTP, suggesting that a 1% increase in precipitation is associated with a 0.019% decrease in HSR's OTP, or approximately 7 additional delayed HST services, *ceteris paribus*. Similarly, the occurrence of thunderstorms in Shanghai was also found to have a significant negative impact on HSR's OTP.

It is worth noting that snow events appear to have a more severe negative impact on HSR's OTP than other weather types. For instance, the occurrence of snowfall in Jinan is found to be associated with a 2.4% decrease in HSR's OTP. Likewise, if snowfall occurs in Nanjing, the OTP of the Beijing- Shanghai HSR is associated with a 10.6% decrease, or 30 additional delayed HST services. In fact, the significance of the variables representing October, November, and December further confirms that the performance of HSR tends to be affected more severely in the winter season than other seasons, which may be attributable to the influences of inclement weather events.

Conversely, Models 3–5 reveal the influences of different weather conditions on the OTP of air arrivals, the number of delayed flights, and the number of cancellations, respectively. The results show that aviation's OTP is influenced by various types of weather events, such as precipitation, fog, thunderstorm, and heavy wind. In addition, the results also show that the magnitude of weather impacts also vary substantially among different cities. For instance, the estimate of precipitation in Nanjing was found to be the largest and most statistically significant in both Models 3 and 4, which suggests that the performance of flights serving this corridor is strongly influenced by the amount of precipitation, *ceteris paribus*. In addition, the occurrence of thunderstorms in Shanghai and Beijing was also found to have negative and significant influences on the OTP of corresponding flights. The result of Model 5 is generally consistent with that of Models 3 and 4. In particular, it confirms that thunderstorms appear to have a strong and significant influence on flight cancellations. In terms of seasonal effects, the analysis reveals that the OTP of aviation tends to be substantially

[3] The weather conditions in Tianjin are not included due to the potential issue of collinearity, which is due to its geographic proximity to Beijing.

[4] We do not evaluate the influence of weather conditions of HSR cancellation due to the fact that there is very few HSR cancellation cases during the period of investigation. As a result, most of the observations would be zero and the analysis may not generate robust estimation outcomes.

Table 5
Regression results of the Beijing-Shanghai Corridor.

Model	Model 1		Model 2		Model 3		Model 4		Model 5	
Dependent Variable	hsrotp		hsrdelay		arrotp		arrdelay		aircancel	
pek_preci	−0.019**	(−2.45)	6.833**	(2.58)	−0.007	(−0.18)	6.933	(0.87)	12.392***	(3.28)
pek_fog	0.004	(0.67)	−1.460	(−0.64)	−0.054*	(−1.67)	11.208	(1.64)	10.008***	(3.08)
pek_thunder	0.003	(0.55)	−1.384	(−0.64)	−0.063**	(−2.08)	12.598**	(1.97)	31.980***	(10.46)
pek_snow	0.006	(0.73)	−1.731	(−0.62)	−0.067*	(−1.67)	12.440	(1.47)	1.114	(0.28)
pek_winda	−0.000	(−0.61)	0.226	(1.05)	−0.006**	(−2.05)	1.412**	(2.18)	0.208	(0.68)
sha_fog	−0.001	(−0.12)	0.374	(0.09)	0.043	(0.76)	−7.876	(−0.66)	−4.443	(−0.78)
sha_thunder	−0.012*	(−1.77)	4.703**	(2.05)	−0.072**	(−2.20)	15.546**	(2.26)	9.191***	(2.81)
sha_snow	−0.007	(−0.26)	1.318	(0.14)	0.034	(0.25)	−9.509	(−0.33)	−1.856	(−0.14)
sha_winda	0.001*	(1.71)	−0.315	(−1.45)	0.001	(0.37)	−0.289	(−0.44)	−0.766**	(−2.48)
nkg_preci	0.006	(0.96)	−1.764	(−0.88)	−0.099***	(−3.44)	24.403***	(4.04)	16.041***	(5.61)
nkg_fog	0.002	(0.34)	−1.050	(−0.60)	0.010	(0.41)	−3.088	(−0.59)	−1.936	(−0.78)
nkg_thunder	−0.004	(−0.58)	1.787	(0.71)	−0.023	(−0.64)	4.215	(0.56)	6.625*	(1.85)
nkg_snow	−0.106***	(−6.22)	30.043***	(5.21)	0.030	(0.37)	−6.219	(−0.36)	1.207	(0.15)
nkg_winda	0.000	(0.21)	−0.058	(−0.21)	−0.003	(−0.80)	0.508	(0.62)	0.353	(0.91)
tna_fog	−0.004	(−0.78)	0.558	(0.29)	−0.040	(−1.44)	6.994	(1.21)	6.118**	(2.23)
tna_thunder	0.003	(0.48)	−1.258	(−0.52)	−0.011	(−0.30)	1.754	(0.24)	19.037***	(5.46)
tna_snow	−0.024**	(−2.10)	8.473**	(2.20)	0.058	(1.06)	−12.254	(−1.06)	1.864	(0.34)
tna_winda	−0.001	(−0.67)	0.104	(0.36)	−0.004	(−0.93)	0.516	(0.60)	−0.334	(−0.82)
prea1	0.001	(0.33)	−0.372	(−0.39)	−0.005	(−0.37)	1.256	(0.44)	1.325	(0.98)
prea2	0.001	(0.48)	−0.885	(−0.91)	−0.010	(−0.72)	1.881	(0.65)	−0.366	(−0.27)
Oct	−0.021***	(−2.69)	3.142	(1.19)	−0.022	(−0.58)	11.352	(1.41)	0.822	(0.22)
Nov	−0.024***	(−2.75)	3.892	(1.33)	0.030	(0.71)	−7.101	(−0.81)	1.616	(0.39)
Dec	−0.023**	(−2.41)	3.840	(1.21)	0.047	(1.04)	−9.926	(−1.04)	4.379	(0.97)
Jan	−0.008	(−0.77)	3.337	(1.01)	0.026	(0.56)	−6.959	(−0.70)	3.392	(0.72)
Feb	0.004	(0.48)	0.398	(0.13)	0.030	(0.69)	−7.601	(−0.82)	3.162	(0.72)
Mar	0.006	(0.71)	−1.477	(−0.56)	−0.009	(−0.23)	0.813	(0.10)	2.130	(0.56)
Apr	0.009	(1.21)	−3.064	(−1.26)	−0.094***	(−2.65)	14.756**	(1.99)	2.977	(0.86)
May	0.012	(1.59)	−4.262*	(−1.72)	−0.052	(−1.50)	11.341	(1.55)	3.449	(1.00)
Jun	0.013*	(1.81)	−4.994**	(−2.00)	−0.156***	(−4.19)	29.474***	(3.79)	13.243***	(3.62)
Jul	0.002	(0.30)	−0.516	(−0.20)	−0.185***	(−4.74)	35.767***	(4.39)	19.256***	(4.99)
Aug	0.003	(0.40)	−0.856	(−0.33)	−0.100**	(−2.54)	20.391**	(2.44)	4.780	(1.22)
Lag.hsrotp	−0.021	(−0.39)								
Lag.hsrdelay			−0.035	(−0.65)						
Lag.arrotp					0.250***	(4.93)				
Lag.arrdelay							0.261***	(5.18)		
Lag.aircancel									0.227***	(6.04)
constant	0.983***	(18.97)	13.265***	(4.76)	0.681***	(11.41)	14.159*	(1.71)	3.951	(1.01)
No. of Obs.	362		362		364		364		364	
DW d-statistic	2.128		2.100		2.005		2.017		2.006	
R-squared	0.309		0.211		0.491		0.495		0.718	

Notes: 1. sha_preci and tna_preci are not included in the analysis due to the concern of collinearity.
2. T-statistics are displayed in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

lower than that of HSR in summer months, which further confirms that the OTP of aviation is more likely to be strongly influenced by severe weather such as thunderstorms and heavy rainfall.

The results also reveal that estimates of the lagged variables are statistically significant only in the case of aviation, which suggests that the lagged effect of aviation delays one day can have a strong influence on OTP the following day. In other words, the impacts of severe weather events on aviation's OTP may be further enlarged due to a strong lagged effect. Conversely, the OTP of HSR is less impacted by its performance the previous day. Hence, the impact of severe weather events on HSR's performance is less extensive than that of aviation.

Overall, the R-squared values range from 0.211 to 0.718, suggesting that the explanatory powers of these models vary from 21.1% to 71.8%. The Durbin–Watson (DW) d-statistics are either equal to 2 or very close to 2 in Models 1–5, indicating that serial correlation is not a concern in the assessments.[5]

The results of the regression analysis examining severe weather impacts on HSR and aviation's performance in the Hangzhou - Shenzhen Corridor are presented in Table 6. Models 6 and 7 summarize the factors that affect OTP and the number of delayed HSR services, respectively. Specifically, the variables representing the amount of precipitation in Shenzhen and the occurrence of thunderstorms in Fuzhou (FOC) were found to be statistically significant (at a 1% significance level), which suggests that severe weather events in these particular cities have a significant impact on the OTP of HSR operating between Hangzhou and Shenzhen. Conversely,

[5] All variables were tested using the Augmented Dickey-Fuller unit-root test. The results, as summarized in Appendix E, suggest that all the variables are stationary.

Table 6
Regression results of the Hangzhou-Shenzhen Corridor.

Model Dependent Variable	Model 6 hsrotp		Model 7 hsrdelay		Model 8 arrotp		Model 9 arrdelay		Model 10 aircancel	
hgh_preci	0.002	(0.52)	−0.102	(−0.19)	0.043	(1.23)	−3.005	(−1.13)	2.681**	(2.31)
hgh_fog	0.008*	(1.94)	−1.244**	(−2.05)	−0.110***	(−2.86)	7.081**	(2.43)	1.493	(1.17)
hgh_thunder	0.000	(0.02)	−0.025	(−0.05)	−0.041	(−1.22)	2.109	(0.83)	0.219	(0.20)
hgh_snow	−0.004	(−0.34)	0.869	(0.49)	−0.013	(−0.11)	4.467	(0.53)	1.228	(0.33)
szx_preci	−0.005***	(−2.63)	0.886***	(2.94)	−0.085***	(−4.50)	6.571***	(4.55)	3.907***	(6.08)
szx_fog	0.000	(0.04)	−0.187	(−0.13)	−0.053	(−0.59)	3.695	(0.54)	1.133	(0.38)
szx_thunder	0.002	(0.70)	−0.455	(−0.86)	−0.111***	(−3.33)	10.533***	(4.14)	3.427***	(3.08)
szx_winda	0.000	(0.11)	−0.019	(−0.31)	0.002	(0.43)	−0.204	(−0.69)	0.564***	(4.35)
foc_preci	−0.006*	(−1.81)	1.017*	(1.87)	−0.071**	(−2.07)	8.474***	(3.26)	1.155	(1.02)
foc_fog	−0.003	(−0.71)	0.448	(0.73)	−0.029	(−0.75)	0.972	(0.33)	3.071**	(2.35)
foc_thunder	−0.009**	(−2.21)	1.157*	(1.81)	−0.110***	(−2.73)	6.278**	(2.04)	−3.819***	(−2.83)
foc_winda	−0.000	(−1.10)	0.064	(1.30)	−0.005	(−1.62)	0.384	(1.62)	−0.217**	(−2.09)
prea1	0.003	(1.51)	−0.575*	(−1.90)	−0.045**	(−2.39)	3.422**	(2.38)	−1.114*	(−1.76)
prea2	0.004	(1.48)	−0.575	(−1.54)	0.012	(0.52)	−1.599	(−0.90)	1.570**	(2.02)
Oct	0.004	(0.97)	−0.455	(−0.68)	0.110**	(2.57)	−8.542***	(−2.63)	−0.557	(−0.40)
Nov	−0.001	(−0.19)	0.547	(0.71)	0.067	(1.38)	−3.296	(−0.89)	−2.236	(−1.39)
Dec	−0.002	(−0.34)	0.722	(0.90)	0.149***	(2.88)	−9.584**	(−2.44)	0.780	(0.46)
Jan	−0.001	(−0.16)	0.868	(1.05)	0.046	(0.88)	−3.906	(−0.98)	3.269*	(1.88)
Feb	−0.007	(−1.33)	2.104**	(2.50)	0.081	(1.53)	−6.906*	(−1.70)	−0.246	(−0.14)
Mar	0.008*	(1.68)	−0.561	(−0.75)	0.015	(0.33)	−0.285	(−0.08)	−1.277	(−0.82)
Apr	0.003	(0.76)	0.457	(0.68)	0.016	(0.38)	0.883	(0.27)	0.345	(0.24)
May	0.006	(1.46)	−0.319	(−0.50)	0.029	(0.73)	−1.447	(−0.48)	2.095	(1.57)
Jun	0.008*	(1.91)	−0.719	(−1.05)	−0.099**	(−2.25)	7.446**	(2.23)	4.768***	(3.23)
Jul	0.006	(1.39)	−0.300	(−0.44)	−0.078*	(−1.79)	5.604*	(1.68)	1.647	(1.14)
Aug	−0.005	(−1.09)	0.903	(1.29)	−0.068	(−1.51)	5.935*	(1.75)	3.895***	(2.64)
Lag.hsrotp	−0.060	(−1.12)								
Lag.hsrdelay			−0.053	(−0.98)						
Lag.arrotp					0.184***	(3.70)				
Lag.arrdelay							0.152***	(3.08)		
Lag.aircancel									0.032	(0.69)
constant	1.048***	(19.77)	1.412**	(2.02)	0.638***	(11.89)	13.338***	(3.77)	−0.471	(−0.33)
No. of Obs.	362		362		364		364		364	
DW d-statistic	1.989		1.993		2.063		2.084		1.850	
R-squared	0.188		0.188		0.404		0.418		0.447	

Notes: 1. szx_snow and foc_snow are not included in the analysis due to the concern of collinearity.
2. T-statistics are displayed in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

the OTP of aviation that serves these three cities was found to be affected more considerably by various weather conditions. For instance, the variables that represent the amount of precipitation and thunderstorms were found to be significant and substantial in Shenzhen and Fuzhou, which can be interpreted as the negative effects of heavy rain and thunderstorms on aviation's OTP tend to be significant if occurring in Shenzhen and Fuzhou, respectively. In addition, the OTP of aviation was also found to be negatively associated with other factors. For instance, air service is likely to experience a delay if the weather in Hangzhou becomes foggy. Likewise, OTP of air service can also decrease if air temperature increases in this region.

In terms of temporal variations, the OTP of aviation and the number of delayed flights were found to be negatively associated with the dummy variables that represent the summer months, which suggests that severe weather events that occur more frequently during summer, such as heavy rainfall and thunderstorms, tend to have a significant disruption on air transport services, whereas the disruption of HSR is likely to be less significant.

Table 7 provides an impact assessment of weather conditions on HSR and aviation, with a focus on the Hefei and Bengbu corridor. One should note there is no aviation serving this corridor given its short distance. Hence, to make a reasonable assessment, the average arrival OTP of all domestic flights originating from the Hefei Xinqiao Airport (HFE) was adopted, given that it is the only major airport that overlaps with the rail corridor. It is clear that in the case of the central-eastern region, the operation of HSR is again less sensitive to most weather conditions except for snow events. Specifically, the OTP of HSR between Hefei and Bengbu is likely to decrease by 5% in snowy weather, *ceteris paribus*. Conversely, the influence of snow on aviation's OTP is insignificant, which suggests that it is less influential in this region. However, other weather conditions such as heavy rainfall and fog were found to have a more considerable influence on aviation's OTP in this region instead, *ceteris paribus*.

In addition, the analysis also confirms that the OTP of different modes of transportation varies seasonally. In particular, the OTP of HSR tends to decrease in February. Conversely, the OTP of aviation generally improves in winter, but may experience major drops during summer. The interpretation of seasonal variation is somewhat complicated, as it can be attributed to various factors. For instance, the occurrence of severe weather events such as heavy rainfall and thunderstorms is likely to drive the decline of aviation's OTP in the summer months, whereas the decrease of the OTP of HSR in February could be due either to snow or the increased travel demand during the Spring Festival.

Table 7
Regression results of the Hefei-Bengbu Corridor.

Model Dependent Variable	Model 11 hsrotp		Model 12 hsrdelay		Model 13 arrotp		Model 14 arrdelay		Model 15 aircancel	
hfe_preci	0.003	(0.44)	−0.159	(−0.32)	−0.049**	(−2.45)	4.942**	(2.58)	0.590	(0.62)
hfe_fog	0.000	(0.06)	−0.013	(−0.03)	−0.036**	(−2.01)	3.118*	(1.81)	0.675	(0.78)
hfe_thunder	−0.002	(−0.34)	0.155	(0.31)	−0.012	(−0.58)	2.019	(1.02)	1.853*	(1.88)
hfe_snow	−0.055***	(−4.90)	4.181***	(4.98)	0.019	(0.57)	−2.137	(−0.65)	−0.377	(−0.23)
hfe_winda	−0.001	(−0.82)	0.047	(0.78)	0.003	(1.12)	−0.255	(−1.08)	−0.153	(−1.29)
hfe_prea	0.005	(0.46)	−0.392	(−0.48)	0.027	(0.82)	−3.012	(−0.95)	0.299	(0.19)
Oct	0.002	(0.29)	0.005	(0.01)	0.064***	(2.62)	−6.983***	(−2.97)	−3.034**	(−2.59)
Nov	0.002	(0.26)	0.053	(0.08)	0.022	(0.88)	−2.460	(−1.01)	−3.287***	(−2.65)
Dec	0.006	(0.68)	−0.298	(−0.44)	0.064**	(2.29)	−6.320**	(−2.38)	−3.388**	(−2.55)
Jan	−0.007	(−0.81)	0.627	(0.91)	−0.018	(−0.63)	1.276	(0.48)	−2.258*	(−1.68)
Feb	−0.017*	(−1.92)	1.341**	(2.03)	−0.000	(−0.01)	−0.495	(−0.19)	−4.522***	(−3.43)
Mar	−0.002	(−0.31)	0.243	(0.41)	0.031	(1.27)	−3.422	(−1.46)	−2.934**	(−2.49)
Apr	−0.003	(−0.38)	0.219	(0.39)	0.008	(0.33)	−0.503	(−0.23)	−1.157	(−1.05)
May	0.008	(1.08)	−0.573	(−1.00)	0.018	(0.80)	−2.128	(−0.97)	−1.307	(−1.19)
Jun	0.000	(0.02)	0.017	(0.03)	−0.134***	(−5.51)	11.947***	(5.18)	2.156*	(1.94)
Jul	0.006	(0.78)	−0.428	(−0.73)	−0.155***	(−6.04)	14.390***	(5.89)	0.465	(0.41)
Aug	−0.001	(−0.18)	0.095	(0.17)	−0.116***	(−4.71)	11.189***	(4.74)	−0.777	(−0.70)
Lag.hsrotp	0.097*	(1.87)								
Lag.hsrdelay			0.094*	(1.82)						
Lag.arrotp					0.160***	(3.05)				
Lag.arrdelay							0.175***	(3.35)		
Lag.aircancel									0.213***	(4.07)
constant	0.739**	(2.23)	12.532	(0.51)	−0.114	(−0.11)	103.480	(1.09)	−2.988	(−0.06)
No. of Obs.	362		362		364		364		364	
DW d-statistic	1.955		1.957		2.076		2.072		2.002	
R-squared	0.132		0.131		0.553		0.575		0.283	

Note: T-statistics are displayed in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

6. Conclusion

This paper addresses two key research questions using HSR and aviation in China as an example – what are the impacts of severe weather events on HSR and aviation delays, and to what extent are HSR and aviation vulnerable to various types of weather events. For the first time, these issues were investigated using a comprehensive dataset that covered the daily weather condition and the OTP of HSR and aviation from October 2016 to September 2017.

Based on data visualization and regression analysis, the study reveals that the OTP of HSR and aviation varies substantially both spatially and temporally, and weather conditions do have a significant impact on their performance. In particular, the OTP of HSR serving the southeast coastal region is found to be more sensitive to heavy rain and thunderstorms than other weather events, whereas snowstorms appear to be more disruptive to HSR performance in the central-eastern and northern regions. In the case of aviation, the results confirm that weather events during summer tend to cause more severe disruptions of air service, whereas the system is disrupted less frequently and less severely during winter months.

These research findings provide at least the following two implications for planning and policy-making. First, given that the operational performance of HSR and aviation under different weather events is quite distinct, transportation planning agencies need to develop appropriate strategies to further improve system resilience of different modes of transportation in order to reduce negative consequences caused by future extreme weather events. Second, given that the impacts of severe weather events on HSR and aviation vary temporally and spatially, future transportation planning needs to facilitate the development of an integrated transportation system to minimize trip disruptions under severe weather events by providing travelers with more flexibility and convenience through a modal substitution.

One should also note that this study has several caveats that need to be further improved in future research. First, the research findings have a limited application as the analysis was only based on three transportation corridors and the dataset only captures a specific time period. Therefore, it would be valuable to expand both the geographic and temporal focuses of the analysis so that research findings could be further validated given the change of the evaluation scope. The other caveat is that the results should be considered preliminary because existing models did not control for other factors that may affect OTP, such as air traffic control, aircraft condition, and technological failure due to data limitation. If such data becomes available in the future, it would be worthwhile reinvestigating the issue with an improved statistical model. Another direction of future research is to integrate the statistical modeling framework with the machine learning technique to achieve OTP forecasting for different transportation systems.

Acknowledgments

We would like to thank the three anonymous reviewers for providing valuable comments for this paper. We also would like to thank VariFlight Technology Co. Ltd. for providing the aviation performance data. Any error or omission is the responsibility of the authors.

Appendix A. Summary statistics of the Beijing-Shanghai corridor

Variable	Note	Obs.	Mean	Std. dev.	Min	Max
hsrotp	OTP of HSR (range: 0–1)	364	0.965	0.030	0.775	1
hsrdelay	No. of delayed high-speed train service	364	12.159	9.555	0	62
arrotp	OTP of air service (range: 0–1)	365	0.732	0.171	0.259	0.981
arrdelay	No. of delayed flights	365	53.041	36.061	3	201
aircancel	No. of cancelled flights	365	15.553	22.868	0	145
pek_preci	Amount of precipitation in Beijing	365	0.048	0.225	0	2.600
pek_fog	Whether or not there is fog in Beijing	365	0.066	0.248	0	1
pek_thunder	Whether or not there is thunderstorm in Beijing	365	0.074	0.262	0	1
pek_snow	Whether or not there is snowstorm in Beijing	365	0.036	0.186	0	1
pek_winda	Whether or not there is heavy wind in Beijing	365	5.721	2.848	2	20
sha_preci	Amount of precipitation in Shanghai	365	0.000	0.000	0	0
sha_fog	Whether or not there is fog in Shanghai	365	0.016	0.127	0	1
sha_thunder	Whether or not there is thunderstorm in Shanghai	365	0.068	0.253	0	1
sha_snow	Whether or not there is snowstorm in Shanghai	365	0.003	0.052	0	1
sha_winda	Whether or not there is a heavy wind in Shanghai	365	8.342	2.898	3	20
nkg_preci	Amount of precipitation in Nanjing	365	0.112	0.284	0	2.050
nkg_fog	Whether or not there is fog in Nanjing	365	0.110	0.313	0	1
nkg_thunder	Whether or not there is thunderstorm in Nanjing	365	0.052	0.222	0	1
nkg_snow	Whether or not there is snowstorm in Nanjing	365	0.008	0.090	0	1
nkg_winda	Whether or not there is a heavy wind in Nanjing	365	5.797	2.482	2	16
tna_preci	Amount of precipitation in Jinan	365	0.000	0.000	0	0
tna_fog	Whether or not there is fog in Jinan	365	0.079	0.271	0	1
tna_thunder	Whether or not there is thunderstorm in Jinan	365	0.058	0.233	0	1
tna_snow	Whether or not there is snowstorm in Jinan	365	0.019	0.137	0	1
tna_winda	Whether or not there is a heavy wind in Jinan	365	4.482	2.083	1	12
prea1	Air pressure related factor 1	365	0.000	0.978	−2.466	2.405
prea2	Air pressure related factor 2	365	0.000	0.976	−2.283	3.030

Source: Authors' calculation.

Appendix B. Summary statistics of the Hangzhou-Shenzhen corridor

Variable	Note	Obs.	Mean	Std. Dev.	Min	Max
hsrotp	OTP of HSR (range: 0–1)	364	0.986	0.017	0.851	1
hsrdelay	No. of delayed high-speed train service	364	2.159	2.588	0	17
arrotp	OTP of air service (range: 0–1)	365	0.720	0.191	0.227	1
arrdelay	No. of delayed flights	365	20.622	14.707	0	104
aircancel	No. of cancelled flights	365	4.619	6.595	0	57
hgh_preci	Amount of precipitation in Hangzhou	365	0.112	0.250	0	2.170
hgh_fog	Whether or not there is fog in Hangzhou	365	0.058	0.233	0	1
hgh_thunder	Whether or not there is thunderstorm in Hangzhou	365	0.085	0.279	0	1
hgh_snow	Whether or not there is snowstorm in Hangzhou	365	0.005	0.074	0	1

szx_preci	Amount of precipitation in Shenzhen	365	0.174	0.499	0	3.900
szx_fog	Whether or not there is fog in Shenzhen	365	0.008	0.090	0	1
szx_thunder	Whether or not there is thunderstorm in Shenzhen	365	0.085	0.279	0	1
szx_snow	Whether or not there is snowstorm in Shenzhen	365	0.000	0.000	0	0
szx_winda	Whether or not there is a heavy wind in Shenzhen	365	7.386	2.613	3	16
foc_preci	Amount of precipitation in Fuzhou	365	0.115	0.291	0	2.050
foc_fog	Whether or not there is fog in Fuzhou	365	0.052	0.222	0	1
foc_thunder	Whether or not there is thunderstorm in Fuzhou	365	0.052	0.222	0	1
foc_snow	Whether or not there is snowstorm in Fuzhou	365	0.000	0.000	0	0
foc_winda	Whether or not there is a heavy wind in Fuzhou	365	8.140	3.732	3	21
prea1	Air pressure related factor 1	365	0.000	0.788	−2.727	2.029
prea2	Air pressure related factor 2	365	0.000	0.785	−1.785	1.771

Source: Authors' calculation.

Appendix C. Summary statistics of the Bengbu - Hefei corridor

Variable	Note	Obs.	Mean	Std. dev.	Min	Max
hsrotp	OTP of HSR (range: 0–1)	364	0.983	0.030	0.627	1
hsrdelay	No. of delayed high-speed train service	364	1.280	2.205	0	28
arrotp	OTP of air service (range: 0–1)	365	0.820	0.126	0.402	1
arrdelay	No. of delayed flights	365	17.071	12.330	0	55
arrcancel	No. of cancelled flights	365	4.896	4.748	0	39
hfe_preci	Amount of precipitation in Hefei	365	0.091	0.235	0	1.850
hfe_fog	Whether or not there is fog in Hefei	365	0.079	0.271	0	1
hfe_thunder	Whether or not there is thunderstorm in Hefei	365	0.058	0.233	0	1
hfe_snow	Whether or not there is snowstorm in Hefei	365	0.019	0.137	0	1
hfe_winda	Whether or not there is a heavy wind in Hefei	365	4.482	2.083	1	12
hfe_prea	Air pressure in Hefei	365	30.019	0.293	29.430	30.640

Source: Authors' calculation.

Appendix D. Correlation matrix of the weather related control variables in the Beijing-Shanghai-Corridor analysis

Variable	pek_preci	sha_preci	nkg_preci	tna_preci	pek_fog	sha_fog	nkg_fog	tna_fog	pek_thunder	sha_thunder	nkg_thunder	tna_thunder
Beijing precipitation (pek_preci)	1											
Shanghai precipitation (sha_preci)	.	.										
Nanjing precipitation (nkg_preci)	0.044	.	1									
Jinan precipitation (tna_preci)	.	.	.	.								
Beijing fog (pek_fog)	−0.048	.	0.021	.	1							
Shanghai fog (sha_fog)	−0.028	.	−0.013	.	0.053	1						
Nanjing fog (nkg_fog)	−0.068	.	0.176	.	0.332	−0.045	1					
Jinan fog (tna_fog)	−0.052	.	−0.043	.	0.249	0.121	0.124	1				
Beijing thunderstorm (pek_thunder)	0.368	.	0.082	.	−0.075	−0.037	−0.066	−0.083	1			
Shanghai thunderstorm (sha_thunder)	−0.002	.	0.340	.	−0.072	−0.035	0.044	−0.080	0.172	1		

Nanjing thunderstorm (nkg_thunder)	0.083	.	0.376	.	−0.062	−0.030	−0.003	−0.069	0.169	0.376	1	
Jinan thunderstorm (tna_thunder)	0.499	.	0.002	.	−0.066	−0.032	−0.049	−0.073	0.245	0.073	0.101	1
Beijing snow (pek_snow)	−0.004	.	0.082	.	0.128	−0.025	0.122	0.053	−0.054	0.006	0.022	0.016
Shanghai snow (sha_snow)	−0.011	.	−0.021	.	−0.014	−0.007	−0.018	−0.015	−0.015	−0.014	−0.012	−0.013
Nanjing snow (nkg_snow)	−0.019	.	−0.002	.	−0.024	−0.012	−0.032	−0.027	−0.026	−0.025	−0.021	−0.023
Jinan snow (tna_snow)	−0.012	.	0.090	.	−0.037	−0.018	−0.049	0.033	−0.040	−0.038	0.147	−0.035
Beijing snow (pek_winda)	−0.037	.	−0.029	.	−0.172	0.096	−0.160	0.040	−0.024	−0.080	0.053	−0.050
Shanghai snow (sha_winda)	0.115	.	−0.019	.	−0.158	−0.075	−0.166	0.000	0.003	−0.092	−0.058	−0.021
Nanjing snow (nkg_winda)	0.104	.	0.162	.	−0.121	−0.050	−0.095	−0.009	−0.070	−0.057	−0.036	0.020
Jinan snow (tna_winda)	0.053	.	−0.001	.	−0.163	0.074	−0.132	−0.146	0.055	−0.089	0.005	0.141
Beijing pressure (pek_prea)	−0.160	.	−0.057	.	0.115	0.146	0.127	0.179	−0.349	−0.217	−0.183	−0.241
Shanghai pressure (sha_prea)	−0.206	.	−0.187	.	0.122	0.065	0.090	0.132	−0.348	−0.299	−0.243	−0.232
Nanjing pressure (nkg_prea)	−0.224	.	−0.180	.	0.118	0.084	0.091	0.149	−0.359	−0.289	−0.239	−0.247
Jinan pressure (tna_prea)	−0.200	.	−0.089	.	0.115	0.123	0.120	0.175	−0.374	−0.240	−0.209	−0.264

Variable	pek_snow	sha_snow	nkg_snow	tna_snow	pek_winda	sha_winda	nkg_winda	tna_winda	pek_prea	sha_prea	nkg_prea	tna_prea
Beijing precipitation (pek_preci)												
Shanghai precipitation (sha_preci)												
Nanjing precipitation (nkg_preci)												
Jinan precipitation (tna_preci)												
Beijing fog (pek_fog)												
Shanghai fog (sha_fog)												
Nanjing fog (nkg_fog)												
Jinan fog (tna_fog)												
Beijing thunderstorm (pek_thunder)												
Shanghai thunderstorm (sha_thunder)												
Nanjing thunderstorm (nkg_thunder)												
Jinan thunderstorm (tna_thunder)												
Beijing snow (pek_snow)	1											
Shanghai snow (sha_snow)	−0.010	1										
Nanjing snow (nkg_snow)	−0.018	−0.005	1									
Jinan snow (tna_snow)	0.189	−0.007	0.209	1								
Beijing snow (pek_winda)	0.003	0.263	0.212	0.154	1							
Shanghai snow (sha_winda)	0.039	0.121	0.157	0.087	0.174	1						
Nanjing snow (nkg_winda)	0.153	0.025	0.179	0.221	0.076	0.577	1					
Jinan snow (tna_winda)	−0.009	0.038	0.066	0.064	0.408	0.064	0.073	1				
Beijing pressure (pek_prea)	0.227	0.063	0.169	0.181	0.122	0.126	0.167	−0.236	1			
Shanghai pressure (sha_prea)	0.143	0.058	0.104	0.088	0.050	0.007	−0.011	−0.210	0.894	1		
Nanjing pressure (nkg_prea)	0.148	0.071	0.133	0.093	0.082	0.042	−0.005	−0.214	0.916	0.991	1	
Jinan pressure (tna_prea)	0.196	0.067	0.166	0.158	0.104	0.133	0.142	−0.246	0.986	0.929	0.952	1

Note: sha_preci and tna_preci have no value due to the existence of collinearity.

Appendix E. Augmented Dickey-Fuller Unit-Root test

Beijing - Shanghai Corridor			Hangzhou - Shenzhen Corridor			Bengbu - Hefei Corridor		
Variable	T-sta.	P-value	Variable	T-sta.	P-value	Variable	T-sta.	P-value
hsrotp	−15.685	0.0000	hsrotp	−17.402	0.0000	hsrotp	−16.08	0.0000
hsrdelay	−17.634	0.0000	hsrdelay	−17.251	0.0000	hsrdelay	−16.152	0.0000
arrotp	−10.64	0.0000	arrotp	−12.319	0.0000	arrotp	−9.519	0.0000
arrdelay	−10.563	0.0000	arrdelay	−12.529	0.0000	arrdelay	−9.15	0.0000
aircancel	−10.162	0.0000	aircancel	−14.18	0.0000	aircancel	−12.492	0.0000
pek_preci	−16.842	0.0000	hgh_preci	−16.584	0.0000	hfe_preci	−17.818	0.0000
pek_fog	−10.848	0.0000	hgh_fog	−14.076	0.0000	hfe_fog	−14.728	0.0000
pek_thunder	−13.657	0.0000	hgh_thunder	−12.973	0.0000	hfe_thunder	−17.378	0.0000
pek_snow	−15.498	0.0000	hgh_snow	−19.132	0.0000	hfe_snow	−14.398	0.0000
pek_winda	−13.383	0.0000	szx_preci	−14.806	0.0000	hfe_winda	−14.173	0.0000
sha_fog	−19.348	0.0000	szx_fog	−19.185	0.0000	hfe_prea	−4.071	0.0011
sha_thunder	−15.103	0.0000	szx_thunder	−14.754	0.0000			
sha_snow	−19.079	0.0000	szx_winda	−10.785	0.0000			
sha_winda	−12.778	0.0000	foc_preci	−15.154	0.0000			
nkg_preci	−16.347	0.0000	foc_fog	−15.172	0.0000			
nkg_fog	−14.997	0.0000	foc_thunder	−17.989	0.0000			
nkg_thunder	−17.989	0.0000	foc_winda	−11.046	0.0000			
nkg_snow	−13.538	0.0000	prea1	−4.385	0.0003			
nkg_winda	−11.848	0.0000	prea2	−5.285	0.0000			
tna_fog	−14.728	0.0000						
tna_thunder	−17.378	0.0000						
tna_snow	−14.398	0.0000						
tna_winda	−14.173	0.0000						
prea1	−6.539	0.0000						
prea2	−7.504	0.0000						

Note: The null hypothesis is that the variable contains a unit root, and the alternative is that the variable is either stationary or was generated by a stationary process.

Appendix F. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2019.01.030.

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